

Leveraging Social Communities for Optimizing Cellular Device-to-Device Communications

Md Abdul Alim, Tianyi Pan, My T. Thai, and Walid Saad

Abstract

Device-to-device (D2D) communications over licensed wireless spectrum has been recently proposed as a promising technology to meet the capacity crunch of next generation cellular networks. However, due to the high mobility of cellular devices, establishing and ensuring the success of D2D transmission becomes a major challenge. To this end, in this paper, a novel framework is proposed to enable devices to form multi-hop D2D connections in an effort to maintain sustainable communication in the presence of device mobility. To solve the problem posed by device mobility, in contrast to existing works, which mostly focus on physical domain information, a durable community based approach is introduced taking social encounters into context. It is shown that the proposed scheme can derive an optimal solution for time sensitive content transmission while also minimizing the cost that the base station pays in order to incentivize users to participate in D2D. Simulation results show that the proposed social community aware approach yields significant performance gain, in terms of the amount of traffic offloaded from the cellular network to the D2D tier, compared to the classical social-unaware methods.

Index Terms

Multi-hop device-to-device communication, optimization algorithm, social community, content delivery.

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I. INTRODUCTION

The demand for wireless data services has increased exponentially in the past decade thus straining the capacity of existing wireless cellular networks [1] and [2]. One promising solution to meet this capacity crunch is to offload cellular traffic via the use of direct device-to-device (D2D) communications for enabling proximity services over the cellular licensed band [3]. To reap the benefits of D2D over cellular, there is a need to optimize and manage the added cellular interference resulting from D2D [4]. However, due to the high mobility of cellular devices, establishing and ensuring the success of D2D transmission is a major challenge.

Recently, there has been an increased interest to operate D2D over cellular using multi-hop transmissions (henceforth referred to as *multi-hop D2D*) [5]–[7]. Such multi-hop D2D architectures can reduce the outage probability while potentially increasing the capacity of D2D communication by alleviating the effect of interference from the cellular users [8]–[10]. Unlike multi-hop ad hoc networks, which do not use the cellular spectrum and do not require any infrastructure, multi-hop D2D is controlled centrally by the base station (BS) for ensuring the QoS of both the cellular and D2D users simultaneously. In cellular multi-hop D2D scenarios, one must properly group the mobile devices in order to achieve the required quality-of-service (QoS). Such a grouping is particularly dependent on the mobility patterns of the devices. One major challenge in the analysis of such mobile, multi-hop D2D pertains to its strong dependence on dynamic human behavior which must be correlated with the complex QoS considerations of the cellular system.

For establishing D2D connections, the cellular BS must provide proper incentives to the users so that they become willing to share their resources for each others transmissions which in turn incurs cost to the BS [11]. Naturally, if most users are unwilling to participate in D2D transmission, the resources cannot be fully utilized, and the operation of the underlaid cellular D2D links will be jeopardized. For real-time content transmission, that must meet stringent latency requirements, a high mobility of the devices will disrupt an ongoing D2D session. This will eventually lead the D2D transmission to fail in delivering the content within the needed time bound. In such cases, the BS must initiate resource consuming cellular connection after dropping the interrupted session, thus reducing the overall network QoS and failing to exploit the benefits of D2D. Consequently, to enable reliable delivery of real-time content over multi-hop D2D at

minimum BS cost, it is imperative to identify a set of reliable devices. Also, such devices must remain within the transmission range of one another during the D2D session to maintain the QoS.

Despite significant research on cellular D2D [2]–[4], there are very few works which consider the cellular multi-hop D2D case. One of the earliest related works is [8] in which the relay selection problem for cellular D2D was studied. In [12], the authors consider D2D communication for relaying user equipment (UE) traffic while introducing a relay selection rule based on interference constraints. The works in [9] and [10] investigate the maximum ergodic capacity and outage probability of cooperative relaying in relay-assisted D2D communication. The results show that multi-hop D2D lowers the outage probability and improves cell edge throughput capacity by reducing the effect of interference from the cellular users. However, none of these works factors in the impact of mobility of devices on the system performance and on the successful delivery of time sensitive contents in particular.

Recently, it has been observed that cellular devices carried by humans exhibit a peculiar pattern with respect to their *physical encounters* both in space and time [13] and [14]. Such social encounters have been shown to exhibit a community structure property which implies that the network can be divided into groups of nodes with dense connections inside each group and fewer connections across groups. From a D2D perspective, users who encounter one another frequently will be likely to form a social community [15]. Additionally, the longer a device stays close to another device, the mutual interaction between them grows further compared to other sporadic contacts. Moreover, a large number of longer duration contacts over a period of time makes the mutual connection more reliable for the continuity of a D2D session which forms the basis of *durable communities*. Leveraging such durable communities for improving D2D transmission constitutes therefore an opportunity that has hitherto not been explored.

The main contribution of this paper is to introduce a new framework that exploits durable social communities to enable successful transfer of a content between two devices with minimum cost using multi-hop D2D. We model the problem as a cost-effective device selection strategy on multi-hop D2D for real-time content delivery. We first formulate the durable community structure and introduce the concept of *sustainable* and *bridge* edges by exploiting the historical encounters of devices. We further propose a novel community detection method based on those previous encounters. Subsequently, we formulate the device selection problem as an optimization

problem and we introduce an efficient method for finding the optimal set of devices on multi-hop path leveraging those social communities. This is in contrast to most existing works on multi-hop D2D that solely focus on system performance [5]–[10]. Simulation results show that our method outperforms classical social-unaware methods significantly on traces generated by the state-of-the-art mobility models. Note that, unlike the more classical case of delay tolerant networks (DTNs) [15], we consider only time sensitive content transfer between source and target with certain delay constraint on the total transmission time. This makes our D2D transmission fundamentally different than the DTN which is opportunistic in nature. In addition, signal interference, resource allocation, noise and fading are intrinsic design parameters in D2D communication underlying cellular networks which makes the design and operation of D2D completely different from DTNs and related ideas such as ad hoc networks.

The rest of the paper is organized as follows. Section II introduces the system while Section III provides the problem formulation. Section IV discusses reliable device selection procedure for multi-hop D2D. Simulation results are analyzed in Section V and conclusions are drawn in Section VI.

II. SYSTEM OVERVIEW AND MODEL REPRESENTATION

A. System Overview

Consider the downlink transmission of an OFDMA cellular network consisting of a single base station (BS) and a set \mathcal{N} of user equipments (UEs). The UEs are able to communicate with one another using D2D links that are underlaid on the cellular network. The total bandwidth \mathcal{B} is divided into F resource blocks (RB) in the set \mathcal{F} . We consider a co-channel network deployment in which \mathcal{B} is shared between cellular and D2D transmissions while considering one RB per UE. We assume UE i requests a content from BS which, in turn, selects UE j ($i, j \in \mathcal{N}$), among other UEs having the content, as the source. The BS will enable direct D2D connections between UE i and UE j when the distance between them is within a desired D2D communication range d_{max} which, in turn, corresponds to a required signal-to-interference-plus-noise ratio (SINR) as shown in Fig. 1(a).

In practice, setting up reliable direct D2D connections while satisfying the quality-of-service (QoS) requirements of both the traditional cellular UEs (CUEs) as well as the D2D UEs is challenging. On the one hand, the unreliable propagation medium and longer distance might

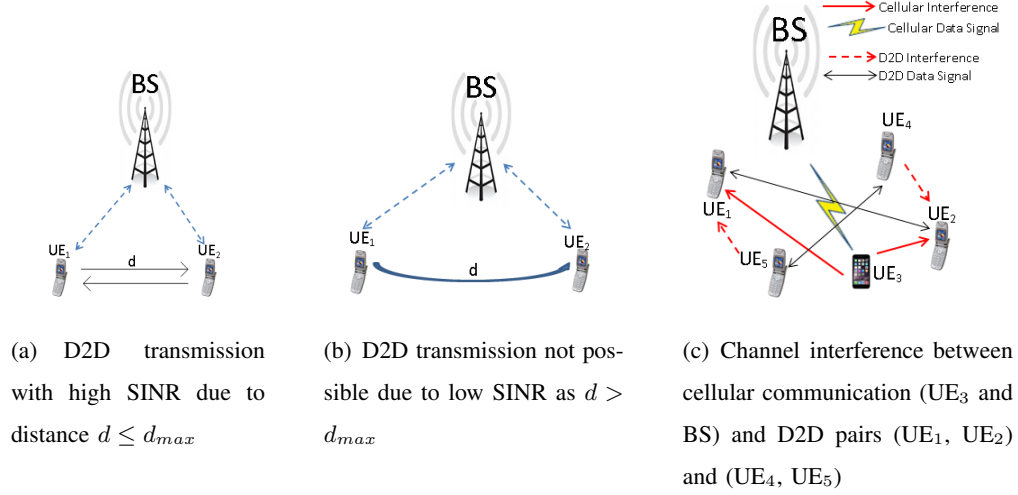


Fig. 1: D2D communication scenario before the transmission takes place

affect the link quality between D2D devices (Fig. 1(b)). On the other hand, interference from other cellular and D2D UEs sharing the same RB will also contribute toward lowering the SINR (Fig. 1(c)). In such low SINR cases, the use of multi-hop D2D communications can be beneficial to enhance the overall D2D QoS.

Indeed, the effectiveness of multi-hop D2D depends on suitable device selection mechanisms. Ideally, for the D2D to successfully sustain data transmission, the devices that are chosen along the multi-hop D2D path must not move beyond the D2D range during a communication session so as to maintain the desired SINR target. Designing such mechanisms is challenging due to the coupling between mobility patterns, incentives for sharing resources, and network QoS. In our model, we focus on selecting a *least cost reliable multi-hop path* for real-time content delivery from a source to a destination. It has been observed that mobility and physical encounter patterns are very closely related to social structures, and very often frequency and length of physical interaction is strongly correlated with proximity [14]. Therefore, we leverage the historical encounter patterns of devices to identify social communities that gives indication on how devices come closer to each other. Thus, the goal of the proposed least cost multi-hop path approach is to select devices based on the social encounters and communities so as to make sure they stay within close proximity of one another during the D2D session.

A flow chart that summarizes the implementation of the proposed scheme is shown in Fig. 2.

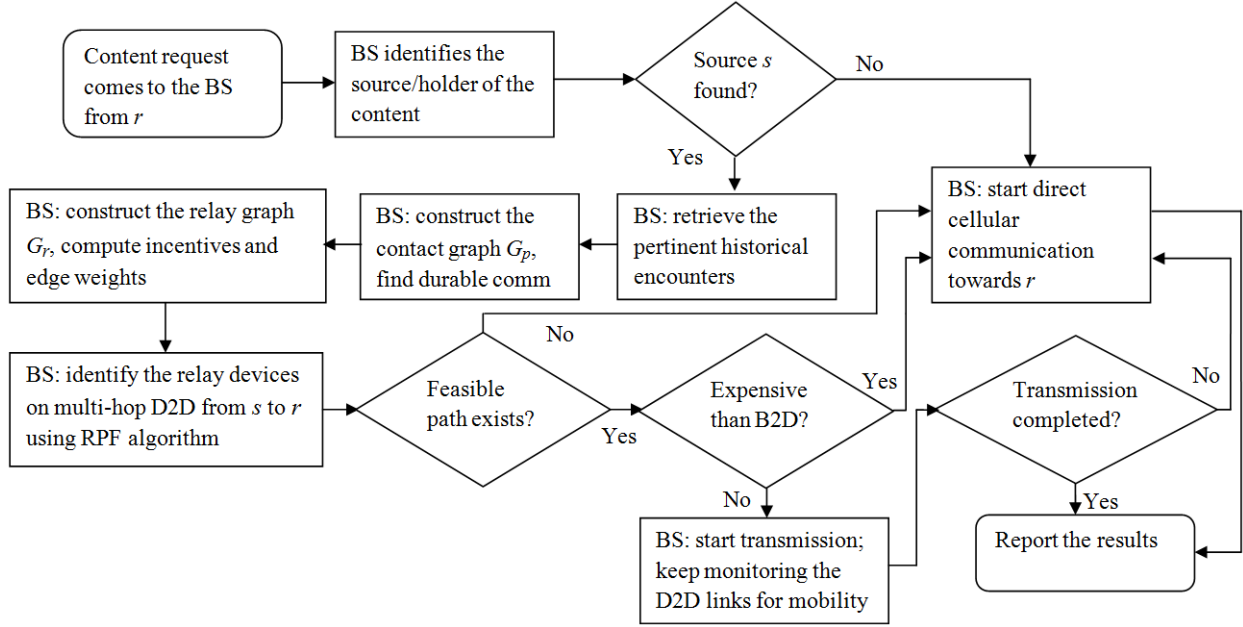


Fig. 2: Flow chart for the proposed solution scheme

Whenever a request for a content comes to the BS from a device r , the BS identifies the source of the content. If no such device is found to hold the content, then, the content is transmitted directly from the BS towards r using cellular communication.

If a device s having the content is identified, the BS initiates the durable community detection phase by invoking the DCD algorithm that is detailed in Subsection III-B2. The BS then assigns proper edge weights to each of the D2D pairs present in its coverage area using the social-based technique that is explained in Subsection IV-B. Finally, the BS identifies the multi-hop D2D path to relay the content from s to r , if there exists any such feasible path that can deliver the content within a certain time threshold t_{max} , instead of; otherwise, the BS initiates a direct cellular connection towards r . In the former case (when a feasible path exists), if the total incentive that the BS has to pay to the relay devices on the multi-hop path is larger than the direct BS to r cost which is termed as *B2D cost*, the BS also initiates a direct cellular connection towards r rather than serving the content via D2D. Once the content transmission starts via multi-hop D2D, the BS keeps track of the pairwise mobility of devices for each hop. If the device mobility leads to a minimum allowable SINR that is below a certain threshold, the multi-hop D2D connection can no longer be sustained. At this point, the BS has to initiate a direct cellular connection towards

r to fulfill its content request. Next, we describe the necessary system model.

B. System Model

In our network, we consider real-time content sharing among mobile D2D users with strict delay requirements. We assume device r requests a content of size b from the BS at time t . The BS identifies s , another UE, as the peer device having the content that would serve the request of r via D2D. There are several approaches to identify a suitable source for a requested content in literature [16] which is not our focus in this paper. Hereinafter, s is referred to as the source device and r as the destination device. However, as discussed previously, these UEs may not be able to communicate directly due to physical constraints and hence a multi-hop path needs to be identified for effective content transfer.

The achievable rate $R_{i,j}$ for the transmission between a device i and device j is

$$R_{i,j} = l_z \log_2(1 + \gamma_{i,j}), \quad (1)$$

where l_z is the bandwidth of RB $z \in \mathcal{F}$ used by i for its data transmission to j , $\gamma_{i,j}$ denotes the SINR for j from i . For the link between i and j , considering signal interference from all other devices using the same RB z , we have

$$\gamma_{i,j} = \frac{p_i g_{i,j}}{\sum_{i' \in \mathcal{Z}, i' \neq i} p_{i'} g_{i',j} + \sigma^2}, \quad (2)$$

where \mathcal{Z} is the set of devices sharing RB z , $g_{i,j}$ is the channel gain between i and j , p_i is the transmit power of device i , and σ^2 is the variance of the Gaussian noise. Here, we note that the BS and the devices operate in a half-duplex mode and the same set of resources (i.e. subcarriers) is shared for transmission of content. In our model, devices on several D2D links can transmit simultaneously and hence can cause interference with one another when using the same RB. However, devices on different hops do not interfere with one another over the same RB. The proposed approach can accommodate any algorithm for allocating RBs to the various D2D and cellular links. Without loss of generality, hereinafter, we adopt graph coloring techniques such as in [17] to perform this assignment. In our model, in line with existing D2D works [7] and for tractability, we do not consider interference on the reverse, acknowledgment link. We

TABLE I: Summary of Important Symbols

Symbol	Description	Symbol	Description
\mathcal{N}	Set of UEs in the network	G_r	Multi-hop D2D graph at time t
\mathcal{B}	Bandwidth of the network	η	Speed of light
\mathcal{F}	Set of RBs	$c_{i,j}$	Cost that BS pays to incentivize i to send content to j
F	Total number of RBs	ψ	Shadowing component
d_{max}	Maximum D2D range	Δt	Historical encounter span
s	Source of the content	t	Actual time when content request is generated from r
r	Destination/requester of the content	G_p	Contact graph
b	Content size	t_c	Time that would have taken to transmit content c of size b from s to r if they were within d_{max}
$R_{i,j}$	Achievable data rate between device i and j	D_{ij}	Encounter duration between device i and j
l_z	Bandwidth of resource block $z \in \mathcal{F}$	δ	Predefined stability threshold
\mathcal{Z}	Set of devices sharing same RB z	$L_i(t)$	Position of device i at time t
$g_{i,j}$	Channel gain between device i and j	\bar{D}_{ij}	Average contact duration between device i and j in Δt
σ^2	variance of the Gaussian noise	$\lambda_{i,j}$	Average number of encounters between i and j
p_i	Transmit power of device i	G^e	Encounter history graph
$\gamma_{i,j}$	SINR at device j for the link $i \rightarrow j$	ζ	Strength threshold
$d_{i,j}$	Distance between device i and j	ρ	Predetermined weight factor
α	Path loss exponent	\mathcal{C}	Set of durable communities
m_0	Fading component	w_{uv}^b	Weight of bridge edge between u and v
$p_{i,j}$	Received power at device j for the link $i \rightarrow j$	w_{uv}^s	Weight of sustainable edge between u and v
$t_{i,j}$	Time required to transmit content from device i to j	$B_{u,v}$	Percentage of actual encounter duration larger than t_c between device u and v
$t_{i,j}^p$	Propagation delay between device i to j	h_C	Durability of community C
$t_{i,j}^x$	Transmission delay from device i to j	k	Number of detected communities

have observed in our experimental evaluation, incorporating reverse link interference into the formulation does not significantly affect the conclusions.

Due to the fact that one cannot know which D2D links will be actively relaying at every hop until we execute our proposed relay path finder (RPF) algorithm described in Section IV, we assume that all the D2D links are active. This enables us to compute the data rate of the links which is required by the RPF algorithm for choosing relays that can deliver the content within t_{max} . In order to reduce the interference between the cellular links and the D2D links, we identify the D2D links which are within close proximity to the cellular link and we ensure

that they do not reuse the same RBs. We only allow those links which are sufficiently far apart to share the same resources. This is essentially similar to the classical frequency reuse concept used in cellular networks, but now we apply to D2D transmissions. For each D2D link (i, j) , we identify the interference set for this link. An interference set for (i, j) contains all the links whose transmitter or receiver are within a certain distance from the transmitter i of the link (i, j) and could potentially cause large interference. In the graph coloring based resource allocation scheme that we use, these links are assigned different resource blocks. Links that are significantly far away from each other are allowed to have same RB. Once the RB allocation is complete, we utilize Eq. (1) and (2) to compute the data rates for each link.

For the wireless network, we consider distance-dependent path loss and multipath Rayleigh fading along with log-normal shadowing. Thus, the received power of each link between devices i and j can be described as $p_{i,j} = p_i \cdot (d_{i,j})^{-\alpha} \cdot |m_0|^2 \cdot 10^{\psi/10}$, where p_i is the transmit power of device i , α is the path loss exponent, m_0 is the fading component, and ψ is the log-normal shadowing component.

Given this SINR model, we now formulate the time required for the transmission between device i and j . The time $t_{i,j}$ in the link (hop) from i to j is defined as

$$t_{i,j} = t_{i,j}^p + t_{i,j}^x = \frac{d_{i,j}}{\eta} + \frac{b}{R_{i,j}}, \quad (3)$$

where $t_{i,j}^p$ is the propagation delay between device i and device j which, in turn, depends on the distance $d_{i,j}$ of the single hop link between i and j , and the speed of light η . The transmission delay, $t_{i,j}^x$, depends on the packet size b and on the achievable data rate for the transmission between i and j as per (1).

To incentivize a certain device i for sharing its resources with another device j , the BS must incur a cost $c_{i,j}$. A device that experiences a good channel and that has a higher transmit power will be able to transfer content more efficiently than others, and hence is a better candidate for D2D from the BS's perspective. Accordingly, we have,

$$c_{i,j} = p_{i,j} = p_i \cdot (d_{i,j})^{-\alpha} \cdot |m_0|^2 \cdot 10^{\psi/10}. \quad (4)$$

This incentive/cost can be in the form of monetary remunerations, coupons, or free data. We summarize most of the important notations used throughout this work in Table I. Next, we define the necessary framework for formulating the problem of identifying reliable devices on multi-hop D2D.

III. PROBLEM FORMULATION AND SOLUTION

A. Problem Formulation

Given this wireless network model, the next goal is to find a set of devices that would enable feasible multi-hop D2D communications while satisfying stringent delay constraints and minimize the BS's cost, as per (4). We introduce the concept of feasible path formally as follows:

Definition 1. (*Feasible Path*) Given a cellular network $G = (\mathcal{V}, \mathcal{E})$, where \mathcal{V} is the set of all devices and \mathcal{E} is the set of links that connects them, a *feasible path* from source s to destination r in G , is an ordering P of devices in \mathcal{V} , where $P = \langle i_1, \dots, i_k \rangle$ such that $i_1 = s$, $i_k = r$, $(i_j, i_{j+1}) \in \mathcal{E}$ and given the interference and mobility of devices, $\sum_{i=1, j=i+1}^k t_{i,j} \leq t_{max}$ where $t_{i,j}$ and t_{max} indicate the time required to transfer a content from i to j and the maximum allowed content sharing time, respectively.

For successful delivery of a content using multi-hop D2D, the devices on a *feasible path* must also remain within a range that corresponds to the desired SINR throughout the D2D session. To combine these properties, we now present the cost-effective device selection problem for multi-hop D2D (CEDS-MD):

Problem 1. (*CEDS-MD*) Cost-effective device selection for multi-hop D2D (CEDS-MD) seeks to identify a *feasible path* P that results in minimum cost of transmission from source s to destination r by minimizing the device cost denoted by $C(P) = \sum_{(i,j) \in P} c_{i,j}$, where $c_{i,j}$ is the cost of BS for incentivizing device i to share resource with device j , and i is the immediate predecessor of j in the feasible path and the devices on P remain within the D2D transmission range throughout t_{max} as governed by the cellular base station.

B. Social Community Aware Cellular Network

Incorporating social based device proximity information with conventional physical layer metrics enables better resource utilization and enhanced traffic offload in D2D [18]. However, these measures are not able to capture the impact of user mobility on the successful completion of D2D transmission particularly when devices are moving rapidly during the transmission. Consequently, there is a need to adopt a more realistic view for the social context by basing it on other social dimensions such as the *actual encounters between users*. Device encounters

have been shown to satisfy the community structure property [14] and thus, the stability of D2D session must be correlated with durable social communities.

Therefore, as a first step towards solving CEDS-MD, we must identify *durable social communities* based on the previous encounter histories. When two devices i and j are within the transmission range d_{max} of each other, they can communicate in D2D mode under the control of the BS. Assuming a content request is generated at a given time t during a day, the BS extracts all the specific historical encounters that start around t in order to realistically predict the mobility pattern of the devices. To this end, the BS constructs a physical contact graph G_p which is a weighted undirected graph and detects the durable communities. Devices belonging to the same community are more likely to have longer contact duration and, hence, they will get more priority to be chosen on the multi-hop D2D if they happen to be within each others proximity at content request time t .

In G_p , each edge represents the average duration of contact between two devices for a certain span Δt of previous days. Δt can be any number of previous days (or hours) depending on the way the encounter histories are being preserved in the BS. If t_c is the time required for the content to be transmitted from s to r when they are within the range d_{max} , the BS will need to consider those previous encounters in Δt that have an average duration of at least t_c . Although encounters having duration at least t_c are good candidates for reliable connections, the longer the duration the more durable it is. To put the duration length into perspective, we not only take into account the encounters having duration of sufficient length (t_c) but also all the previous encounters with duration $D_{ij} \geq (1 + \delta)t_c$ where the stability threshold, $\delta \geq 0$, is a user controlled parameter that reflects the importance of the duration length of encounters beyond t_c . At the same time, we also emphasize on the impact of encounter rates of two devices in Δt paired with the duration. Next we will formally define the notions related to encounters.

1) *Community Structure and Durable Community*: Now, we introduce the necessary terms to describe encounters in the context of D2D and formally define the notion of a durable community structure in this subsection.

Assume that i and j come into the communication range at time t_e , that is, $||L_i(t_e^-) - L_j(t_e^-)|| > d_{max}$ and $||L_i(t_e) - L_j(t_e)|| \leq d_{max}$, where t_e^- denotes the time before t_e , $L_i(t)$ the position of user i at time t , d_{max} the D2D transmission range as determined by the BS and $||\cdot||$ the distance measure. With this, we can define the D2D contact duration:

Definition 2. The *D2D contact duration* between users i and j is defined as the time during which they are in contact before moving out of the range, that is, $D_{ij} = t - t_e$ with $\min_{t-t_e} \{t : \|L_i(t) - L_j(t)\| > d_{max}, t > t_e\}$, where t and t_e are in the continuous time scale.

Consider a series of q contact durations $D_{ij} = (D_{ij}^1, \dots, D_{ij}^q)$ between nodes i and j in time frame Δt , then, we can make the following definition:

Definition 3. The *average contact duration*, denoted by $\bar{D}_{ij} = \frac{\sum_{k=1}^q D_{ij}^k}{q}$, is the expected time during which two devices stay within d_{max} before they move apart again once after coming in proximity to one another.

Next, let $G^e = (\mathcal{V}, \mathcal{E}^e, \mathbf{T})$ be an undirected graph representing the physical encounters of $|\mathcal{V}|$ mobile devices. \mathcal{E}^e is the set of undirected relationships (in this case encounters). Each edge E_i^e has an associated collection of two-dimensional vectors denoted by $\mathbf{T}_i = (T_{i_1}, T_{i_2}, \dots)$. Each element of in \mathbf{T}_i denotes contact time and corresponding duration in Δt time span, i.e., $T_{ij} = \langle t_{uv}, D_{uv} \rangle$ for all the j encounters between device u and v in Δt .

Contact Graph: The request for a content is generated at time t and t_c is the time required to transmit the content from s to r if they are within range d_{max} . We construct an undirected and weighted contact graph $G_p = (\mathcal{V}_p, \mathcal{E}_p, \mathcal{W}_p)$, where $|\mathcal{V}_p| = n$ and $|\mathcal{E}_p| = m$. In doing so, we consider only those encounters in G^e that have *average contact duration* \bar{D}_{ij} sufficiently long enough to cater t_c starting at t , i.e., $\bar{D}_{ij} \geq (1 + \delta)t_c$ where $\delta \geq 0$ is the predefined stability threshold. $w_{uv} \in \mathcal{W}_p$ is the weight function on each edge $(u, v) \in \mathcal{E}_p$ where $u, v \in \mathcal{V}_p$.

Weight Assignment in G_p : Encounters having average contact durations larger than t_c are very good candidates for sustainable D2D transmission. However, considering only the average duration might result in choosing some encounters having a large number of less than t_c duration which will negatively impact the reliable device selection for multi-hop D2D. To account for this in assigning \mathcal{W}_p , we will prioritize those edges having encounters with actual duration larger than t_c with more weight. To this end, we define B_{uv} , $0 \leq B_{uv} \leq 1$ that denotes the percentage of times the encounter duration was actually larger than t_c . Accordingly, we define the weight $w_{uv} = \rho B_{uv} \cdot \lambda_{uv} + (1 - \rho) \bar{D}_{uv}$ where ρ , $0 \leq \rho \leq 1$ is a predefined weight factor that signifies how much emphasis should be put on the average encounter duration with respect to the percentage of times the encounter duration was actually larger than t_c as denoted by B_{uv} . To account for the

encounter rate we have multiplied B_{uv} by the weight factor λ_{uv} , so that the impact of frequent long duration contacts can also be captured in the edge weight. λ_{uv} denotes the average number of encounters between u and v over the time period Δt .

Next, we will define a durable community structure that will group devices having similar contact duration together. Such a structure has special properties related to bridge and sustainable edges. In fact, an edge (u, v) in G_p is said to be *bridge* edge if it has small percentage of successful contact durations B_{uv} which is reflected by $w_{uv} < \zeta$ where ζ is the predefined strength threshold. A *sustainable* edge (u, v) is defined to have large percentage of successful contact durations B_{uv} which is reflected by $w_{uv} \geq \zeta$. We denote the weight of sustainable and bridge edges as w_{uv}^s and w_{uv}^b , respectively. We leverage these edge weights in deciding the relay devices which we describe in Subsection IV-B.

Consequently, a *durable community structure*, denoted by $\mathcal{C} = \{C_1, C_2, \dots, C_k\}$, is a collection of k subsets of \mathcal{V} satisfying $\cup_{i=1}^k C_i = \mathcal{V}$. We say that, a collection of nodes $C_i \in \mathcal{C}$ and its induced subgraph is a *durable community* in G_p if nodes inside C_i are connected primarily through sustainable edges and nodes across communities C_i and C_j , if connected, will have bridge edges. Next, we propose an approach to detect durable communities in G_p .

2) *Durable Community Detection*: For a node $u \in \mathcal{V}_p$, let \mathcal{A}_u be the set of neighbors adjacent to u . Moreover, let w_u be the weight corresponding to this set. For any $C \subseteq \mathcal{V}_p$, let C^{in} and C^{out} be, respectively, the set of links having both endpoints in C and the set of links heading out from C . Additionally, let $w_C = \sum_{(u,v) \in C^{in}} w_{uv}$, $w_C^{out} = \sum_{(u,v) \in C^{out}} w_{uv}$ and $w_C^+ = w_C + w_C^{out}$.

Given the contact graph G_p , we seek to find a community structure $\mathcal{C} = \{C_1, C_2, \dots, C_k\}$ that would strive to group sustainable edges inside a community and place bridge edges across communities. Intuitively, any grouping that maximizes the ratio of sustainable edges to bridge edges inside a community achieves our objective. Thus, we define the *durability* of a community C as $h_C = \frac{w_C}{w_C^+}$, and we formulate the following Durable Community Detection (**DCD**) optimization problem:

$$\begin{aligned}
& \text{maximize } \mathcal{R} = \sum_{C \in \mathcal{C}} h_C = \sum_{C \in \mathcal{C}} \frac{w_C}{w_C^+}, \\
& \text{s.t. } C_i \cap C_j = \emptyset \quad \forall i, j \in \{1, 2, \dots, k\}, \\
& \quad \bigcup_{i=1}^k C_i = \mathcal{V}_p
\end{aligned}$$

In this formulation, the number of communities k is determined by optimizing the objective function \mathcal{R} and is not an input parameter. Next, we show the following properties of network communities identified by optimizing our suggested metric \mathcal{R} : (i) links within a community have high durability contribution and (ii) links connecting communities have low durability contribution.

Proposition 1. *Let $\mathcal{C} = \{C_1, C_2, \dots, C_k\}$ be a community structure detected by optimizing \mathcal{R} , links within each C_i are of strong durability contribution while those connecting communities are of weak durability contribution.*

Proof: For any node $u \in \mathcal{V}_p$ and subset $S \subseteq \mathcal{V}_p$, let $w_{u,S}$ be the total weight of all links that u has towards S and vice versa. By this definition, we obtain $w_u = w_{u,S} + w_{u,\mathcal{V}_p \setminus S}$.

Consider a community $C \in \mathcal{C}$, $u \in C$ and $v \notin C$. Since v is not a member of C , we have

$$\frac{w_C}{w_C^+} > \frac{w_C + w_{v,C}}{w_C^+ + w_v} = \frac{w_C + w_{v,C}}{w_C^+ + w_{v,C} + w_{v,\mathcal{V} \setminus C}},$$

because otherwise adding v to C will give a better value of \mathcal{R} . This equality results in

$$\frac{w_{v,C}}{w_v} < \frac{w_C}{w_C^+},$$

which, in turn, implies that the links joining v to C are insignificant in terms of durability contribution with respect to the total weight of C as a whole.

Similarly, for any node $u \in C$, we have

$$\frac{w_C}{w_C^+} > \frac{w_C - w_{u,C}}{w_C^+ - w_u} = \frac{w_C - w_{u,C}}{w_C^+ - w_{u,C} + w_{u,\mathcal{V} \setminus C}},$$

because otherwise excluding u from C will give a better estimation of \mathcal{R} . This inequality simplifies to

$$\frac{w_{u,C}}{w_u} > \frac{w_C}{w_C^+},$$

which shows that the links joining u to C are of significant weight having larger durability contribution in comparison to the total internal weight of C . ■

3) *A greedy algorithm for DCD problem:* Solving the DCD problem is NP-hard as shown by a similar reduction to modularity as in [19]. Consequently, a heuristic approach that can provide a good solution in a timely manner is more desirable. In this regard, we propose a greedy algorithm for the DCD problem consisting of three phases, shown in Alg. 1.

The first phase, referred to as the *development phase*, identifies raw communities in the input network. Initially, all nodes are unassigned and do not belong to any community. Next, a random node is selected as the first member of a new community C , and consequently, new members who help to maximize C 's durability, h_C , are gradually added into C . When there is no more node that can improve this objective of the current community, another new community is formed and the whole process is then continued in the very same manner on this newly formed community.

Next, the *augmentation phase* rearranges nodes into more appropriate communities. In the first phase, new members are added into a community C in a random order. Therefore, C 's objective value h_C can further be improved if some of its members, that reduce the total durability, are excluded. Such nodes then form singleton communities. This step requires the re-evaluation of all C 's members as a result. The removal of such nodes creates more cohesive communities having higher internal connectedness.

In the last phase, the *refinement phase*, global stability of the whole network is re-estimated. This phase looks at the merging of two adjacent communities in order to improve the overall objective function. If two communities have a large number of mutual connections between them, it is thus more durable to combine them into one community.

The run time complexity of the *development* and *augmentation* phases are $\mathcal{O}(nm)$. Moreover, even though the refinement phase might take $\mathcal{O}(n^3m)$ time in the worst case scenario, we have found that the DCD algorithm computes the durable communities within milliseconds even for networks containing hundreds of nodes as reported in Table II. Since the optimal solution takes exponential time for larger instances of the network, we use smaller values of n in order to obtain results for optimal solution for comparing with the running time of DCD. We formulated the DCD problem as an integer program with quadratic constraints and objective function and solved it using CPLEX [20] to obtain the result for optimal solution. We have reported the results of run time comparison in the Table III. Clearly, the run time complexity of the optimal

Algorithm 1 DCD algorithm

Data: Network $G_p = (V_p, E_p, W_p)$

Result: Durable community structure \mathcal{C}

Phase I: Development Phase.

Initialize $\mathcal{C} \leftarrow \emptyset$

Initialize $Q \leftarrow \mathcal{V}_p$

while \exists unassigned node $x \in Q$ **do**

$C \leftarrow \{x\}$

$Q \leftarrow Q \setminus \{x\}$

while $\exists y \in Q$ such that $h_{C \cup \{y\}} > h_C$ **do**

$y \leftarrow \underset{y \in Q}{\operatorname{argmax}} \{h_{C \cup \{y\}}\}$

$C \leftarrow C \cup \{y\}$

$Q \leftarrow Q \setminus \{y\}$

$\mathcal{C} \leftarrow \mathcal{C} \cup \{C\}$

Phase II: Augmentation Phase.

for $C \in \mathcal{C}$ **do**

while $\exists x \in C$ such that $h_{C \setminus \{x\}} > h_C$ **do**

$C \leftarrow C \setminus \{x\}$

$\mathcal{C} \leftarrow \mathcal{C} \cup \{C\}$

Phase II: Refinement Phase.

while $\exists C_1, C_2$ such that $h_{C_1 \cup C_2} > h_{C_1} + h_{C_2}$ **do**

$(C_1, C_2) \leftarrow \underset{C_1, C_2 \in \mathcal{C}}{\operatorname{argmax}} \{h_{C_1 \cup C_2} - h_{C_1} - h_{C_2}\}$

$\mathcal{C} \leftarrow (\mathcal{C} \setminus \{C_1, C_2\}) \cup \{C_1 \cup C_2\}$

Return \mathcal{C}

algorithm increases exponentially as the number of devices increases in the network, whereas DCD takes only a small amount of time on all of those cases which makes DCD suitable for real-time relay selection.

TABLE II: Running times in seconds for DCD

Method	User count (n)					
	20	50	80	110	140	170
DCD	0.006	0.022	0.05	0.018	0.27	0.84

TABLE III: Comparison of running times in seconds

Method	User count (n)				
	10	15	20	25	30
DCD	0.006	0.005	0.006	0.005	0.009
Optimal	1.68	6.31	422.73	1465	2970

IV. COST-EFFECTIVE DEVICE SELECTION

Once content request is generated at time t , the BS initiates a centralized process that encompasses two tasks. First, it constructs G_p and finds out durable communities as described in previous section. In the second step, the BS selects a set of devices to solve the **CEDS-MD** problem defined in Problem 1. To ensure high likelihood of the successful delivery of content through D2D, the BS incorporates the social encounter based community information as described subsequently.

A. Relay Graph Construction

The BS initiates the second step for device selection by constructing a *multi-hop D2D graph* $G_r = (\mathcal{V}_r, \mathcal{E}_r, \mathcal{W}_c, \mathcal{W}_e)$ where \mathcal{V}_r is the set of devices present at time t . \mathcal{W}_c denotes the BS cost, for any $(i, j) \in \mathcal{E}_r$, $c_{i,j}$ indicates how much incentive BS has to spend in order to make device i agree to share its resources with device j for relay purpose as defined in (4). We put an edge between two devices i and j if and only if the distance between them is within the D2D communication range, that is, the SINR from i to j is above a certain threshold as determined by the BS. Here, the BS is also considered as part of the graph where it is represented by a vertex. The edge connecting the BS and each device has a cost that pertains to the physical channel condition between them. Since a transmitting device in a D2D pair with better channel condition is preferred from the BS's point of view, the BS will pay a higher incentive and thus, it incurs more cost to the BS which is captured in equation (4). In contrast, for a direct BS to device connection, a receiving device having better channel condition with the BS will require less physical resource blocks for the transmission which will result in a smaller B2D cost. The BS will have to use a relatively large number of resource blocks to transmit the content within t_{max} to a device which is far away from it which is essentially a device experiencing poor channel

condition at the BS. Consequently, the cost for BS to that device, termed as *B2D* cost, will be naturally higher than a device with better channel condition. In summary, the B2D cost can be defined to be inversely proportional to the radio channel condition from the BS to that device as denoted below.

$$c_{BS,j} = \frac{K}{p_{BS,j}} = K \times \{p_{BS} \cdot (d_{BS,j})^{-\alpha} \cdot |m_0|^2 \cdot 10^{\psi/10}\}^{-1}. \quad (5)$$

A device located closer to the BS essentially experiences better channel condition at the BS and incurs less B2D cost to receive the content. The inverse of the numerical value of the received signal at device j from the BS, denoted by $p_{BS,j}$ is a large number; the constant $K < 1$ is thus required to normalize the cost so that the B2D cost is in the same scale with the multi-hop D2D cost. To account for the mobility of the devices on the multi-hop path, i.e., increasing the likelihood of successful content delivery, we resort on identified *durable communities* for the assignment of edge weight \mathcal{W}_e described below.

B. \mathcal{W}_e weight assignment in G_r

Since the durable communities are constructed based on physical encounter history, users belonging to the same community have strong connections internally that not only help in reliable content transfer but also lay the basic foundation for stable and sustainable encounter predictions. The BS follows specific rules in order to assign proper edge weights W_{ij} between two devices i and j who are within d_{max} in G_r according to their membership in the durable communities obtained from the contact graph G_p . (i) Devices belonging to same community as well as connected via sustainable edge will have small weight that is inversely proportional to the total internal edge weight of that community. (ii) Devices belonging to same community but either connected with a bridge edge in G_p or without any edge in G_p will have larger weight in G_r compared to case (i). (iii) If devices belong to different communities C_i and C_j and there is no edge connecting them in G_p or the edge connecting them is a bridge edge in G_p , the edge connecting them in G_r will have large weight that is inversely proportional to the weight of the edge bearing minimum weight among all edges connecting C_i and C_j in G_p . If there is no edge connecting C_i and C_j in G_p , we assign W_{ij} the value which is the maximum weight between any two devices in G_r . (iv) If devices belong to different communities C_i and C_j and a sustainable edge connects them in G_p , the edge weight W_{ij} between i and j in G_r will be smaller than that

of case (iii). According to these four criteria, edge weights are assigned between adjacent devices (within d_{max}) in G_r which help our proposed solution RPF to choose suitable relay devices for multi-hop content transfer as we will demonstrate in the performance evaluation section.

C. Social Community Aware Device Selection for Multi-hop D2D

The goal is to find a least cost path from s to r in relay graph G_r within practical constraints of maximum delivery time imposed as part of latency which puts a limit on the number of relay devices. At the same time, we emphasis on the importance of incorporating durable communities into decision making process of device selection for successful D2D session completion. To take this into account, we modify the cost of the path P in Problem 1 as part of our solution to *CEDS-MD*. Accordingly, we include the edge weight W_{ij} that was computed in Section IV-B, to obtain the total cost w_{ij} between i and j as follows:

$$w_{ij} = W_{ij} + c_{i,j}. \quad (6)$$

Note that, both the terms in the right hand side of (6) are normalized and of the same order of magnitude. For real-time content sharing with D2D communication, we can formulate the optimal relay selection problem in multi-hop D2D cellular network as the following optimization problem. Let the variable x_{ij} represent each edge $(i, j) \in E_r$:

$$x_{ij} = \begin{cases} 1, & \text{if } e(i, j) \text{ is selected for least cost feasible path.} \\ 0, & \text{otherwise.} \end{cases} \quad (7)$$

We have the following Integer Program (IP):

$$\min \sum_{(i,j) \in E} w_{ij} x_{ij} \quad (8)$$

$$s.t. \sum_{(i,j) \in E} f_{ij} - \sum_{(k,i) \in E} f_{ki} = \begin{cases} 1 & i = s, \\ -1 & i = r, \\ 0 & \forall i \in V, i \neq s, t, \end{cases} \quad (9)$$

$$\sum_{(i,j) \in E} t_{i,j} x_{ij} \leq t_{max}, \quad (10)$$

$$x_{ij} \in \{0, 1\}, \quad \forall (i, j) \in E. \quad (11)$$

(9) ensures that the selected cost-effective devices constitute a path. The time for transmission between devices i and j is obtained considering cellular and the wireless channel as in (3). (10) makes sure that the selected devices deliver the time-sensitive content within the maximum allowable time t_{max} with high likelihood. This optimization problem is NP-complete since it belongs to a class of combinatorial optimization [21]. Therefore, we cannot derive the optimal solution in polynomial time. Next, we introduce the proposed approach to solve the CEDS-MD problem.

D. Solving the Optimization Problem

We solve the CEDS-MD problem in three steps: (i) relax the IP formulation into a linear program (LP) and solve it, (ii) show that the optimal solution of the LP has at most two fractional paths that will be constructed and (iii) formulate a new LP by adding new constraints. Then, we keep solving the modified LP until it becomes infeasible. This approach obtains the optimal solution in near polynomial time by using interior point method in solving the LP. We start by relaxing (11) to obtain the LP:

$$\min \sum_{(i,j) \in E} w_{ij} x_{ij} \quad (12)$$

$$s.t. \sum_{(i,j) \in E} f_{ij} - \sum_{(k,i) \in E} f_{ki} = \begin{cases} 1 & i = s, \\ -1 & i = r, \\ 0 & \forall i \in V, i \neq s, t, \end{cases} \quad (13)$$

$$\sum_{(i,j) \in E} t_{i,j} x_{ij} \leq t_{max}, \quad (14)$$

$$0 \leq x_{ij} \leq 1 \quad \forall (i,j) \in E. \quad (15)$$

1) *Property of LP Solution:* We denote the LP relaxation of (15) as \mathcal{P} . The optimal solution of \mathcal{P} is no longer integral as in the classical shortest path problem [22], due to the addition of constraint (10). However, the following theorem holds true.

Theorem 1. *There exists either an optimal solution for \mathcal{P} that contains at most two fractional s, r paths or \mathcal{P} is infeasible.*

Proof: Denote P_{sr} as the collection of all s, r paths. Denote $w_{p_j}, t(p_j)$ as the total weight

and total delay of a path $p_j \in P_{sr}$, respectively. p_j is called a long-delay path if $t(p_j) > t_{max}$ and is called a short-delay path otherwise.

We will show that if \mathcal{P} is feasible and an optimal solution \mathbf{x}^* contains more than two fractional s, r paths, then either \mathbf{x}^* can be transformed to an optimal solution with at most two s, r paths or \mathbf{x}^* is not optimal. Assume \mathbf{x}^* contains $k > 2$ fractional paths and is optimal. It is clear that some short-delay paths must be included, otherwise \mathbf{x}^* is not even feasible. Therefore, the problem can be categorized into three cases: i) all paths are short-delay paths, ii) at least two short-delay paths and a long-delay path exist and iii) at least two long-delay paths and a short-delay path exist.

In the first case, if all the short-delay paths selected have the same weight, an equivalent solution can be constructed by assigning flow of 1 to one of the selected paths and flow of 0 to all the others. Such an optimal solution has only one path. If the weight of the selected paths are different, by shifting the flow from heavy-weight paths to light-weight paths can improve the solution and hence, \mathbf{x}^* is not optimal.

In the second and the third case, the weight of long-delay paths must be smaller than short-delay paths or we can shift the flow to short-delay paths and improve the solution. Denote the collection of all selected paths as $P_{\mathbf{x}^*}$, we must have $\sum_{p_j \in P_{\mathbf{x}^*}} f_j t(p_j) = t_{max}$, where f_j is the flow assigned to path p_j . If the total time is less than t_{max} , it is possible to shift flows from short-delay paths to long-delay paths and improve the solution. In the second case, denote p_1, p_2 as two short-delay paths. Also, let p_a as a representation of all other selected paths, where

$$\begin{aligned} f_a &= \sum_{p_j \in P_{\mathbf{x}^*}, j \neq 1, 2} f_j, \\ t(p_a) &= \frac{\sum_{p_j \in P_{\mathbf{x}^*}, j \neq 1, 2} f_j t(p_j)}{f_a}, \\ w(p_a) &= \frac{\sum_{p_j \in P_{\mathbf{x}^*}, j \neq 1, 2} f_j w(p_j)}{f_a}. \end{aligned}$$

Clearly, $f_a t(p_a) + f_1 t(p_1) + f_2 t(p_2) = t_{max}$,

$$f_a w(p_a) + f_1 w(p_1) + f_2 w(p_2) = Y^*,$$

where Y^* denotes the objective value of solution \mathbf{x}^* . Also, we have $t(p_a) > t_{max}, w(p_a) < w(p_1), w(p_2)$.

Without loss of generality, let $t(p_1) < t(p_2)$, then $w(p_1) > w(p_2)$ or p_1, p_2 cannot coexist in

the optimal solution. Consider two moves: (1) Remove p_2 from the optimal solution. (2) Remove p_1 from the optimal solution. For both moves, the solutions are recalculated by assigning flows to the remaining selected paths. Denote the objective value by Y^1, Y^2 for move (1) and (2) respectively. We will show that it is impossible to have both $Y^1, Y^2 \leq Y^*$ and Y^* is not an optimal solution.

After move (1), the following formulas hold.

$$\begin{aligned} t_{max} &= (f_a + \delta_1)t(p_a) + (f_1 + f_2 - \delta_1)t(p_1), \\ Y^1 &= (f_a + \delta_1)w(p_a) + (f_1 + f_2 - \delta_1)w(p_1), \\ \delta_1 &= f_2 \frac{t(p_2) - t(p_1)}{t(p_a) - t(p_1)}. \end{aligned}$$

Therefore,

$$\begin{aligned} \Delta_1 = Y^1 - Y^* &= f_2(w(p_1) - w(p_2)) + \delta_1(w(p_a) - w(p_1)) \\ &= f_2((w(p_1) - w(p_2)) + \frac{t(p_2) - t(p_1)}{t(p_a) - t(p_1)}(w(p_a) - w(p_1))). \end{aligned}$$

After move (2), the following formulas hold.

$$\begin{aligned} t_{max} &= (f_a - \delta_2)t(p_a) + (f_1 + f_2 + \delta_2)t(p_2), \\ Y^2 &= (f_a - \delta_2)w(p_a) + (f_1 + f_2 + \delta_2)w(p_2), \\ \delta_2 &= f_1 \frac{t(p_2) - t(p_1)}{t(p_a) - t(p_2)}. \end{aligned}$$

Therefore,

$$\begin{aligned} \Delta_2 = Y^2 - Y^* &= f_1(w(p_2) - w(p_1)) - \delta_2(w(p_a) - w(p_2)) \\ &= f_1((w(p_2) - w(p_1)) + \frac{t(p_2) - t(p_1)}{t(p_a) - t(p_2)}(w(p_2) - w(p_a))). \end{aligned}$$

Assume $\Delta_1, \Delta_2 > 0$, since $f_1, f_2 > 0$, we have

$$\frac{w(p_1) - w(p_2)}{w(p_1) - w(p_a)} > \frac{t(p_2) - t(p_1)}{t(p_a) - t(p_1)}, \quad (16)$$

$$\frac{w(p_1) - w(p_2)}{w(p_2) - w(p_a)} < \frac{t(p_2) - t(p_1)}{t(p_a) - t(p_2)}. \quad (17)$$

However, inequality (16), (17) cannot both hold simultaneously. To see it clearly, let

$$a = w(p_1) - w(p_2), \quad b = w(p_2) - w(p_a), \quad (18)$$

$$c = t(p_a) - t(p_2), \quad d = t(p_2) - t(p_1). \quad (19)$$

Then, inequality (16) reduces to $\frac{a}{a+b} > \frac{d}{c+d}$, while inequality (17) reduces to $\frac{a}{b} < \frac{d}{c}$. The first one implies $ac > bd$ while the second one implies $ac < bd$.

Therefore, in the second case in which there exists two or more short-delay paths in the solution, we can always perform move (1) or (2) to reduce number of short-delay paths without increasing objective value. The same claim holds true for the third case with a similar reasoning.

In conclusion, we can always create an optimal solution for \mathcal{P} while selecting at most two s, r paths. ■

E. Exact Solution by Cutting Plane

Based on Theorem 1, an optimal solution with at most two fractional paths can always be generated by solving \mathcal{P} . The case of only one path is trivial since it is already the optimal integral solution and no further work is required. Therefore, we are only interested in solutions with two fractional paths. Clearly, the two paths must be one short-delay path, denoted as p_s and one long-delay path, denoted as p_l . Since any feasible integral solution must be a short-delay path, we are particularly interested in p_s . Denote $X_{p_s} = \sum_{(i,j) \in p_s} \bar{x}_{ij}$, where \bar{x}_{ij} is the value of x_{ij} in the current solution. If we cut the path p_s out of the feasible region of \mathcal{P} , the solution must explore other paths by adding the following constraint

$$\sum_{(i,j) \in p_s} x_{ij} < X_{p_s} \quad (20)$$

By resolving \mathcal{P} iteratively while updating the constraint (20), the feasible region of \mathcal{P} is gradually decreased. We continue the iteration until it is infeasible.

The optimal solution will then be the short-delay path with minimum weight. The final algorithm, which we call relay path finder (**RPF**), is presented in Alg. 2.

V. PERFORMANCE EVALUATION

For our simulations, the mobility trace for nodes is generated by self-similar least action walk model (SLAW) which is shown to be very realistic in capturing user mobility [23]. In particular, SLAW generated traces are shown to be effective in representing social contexts present among people sharing common interests or those in a single community such as university campus, companies and theme parks. In human mobility, people strive to reduce the distance of travel by visiting all the nearby destinations before visiting farther destinations unless some high priority

Algorithm 2 RPF: An optimal algorithm for finding least cost relay path

Data: Network $G_r = (V_r, E_r, W_v, W_e)$, source s , target r and t_{max}

Result: A path comprising a set S of edges forming the relay

Initialize $Q \leftarrow \emptyset$

Solve the LP in (8)-(15)

$P \leftarrow$ solution of LP

while P is feasible **do**

$F \leftarrow \{\text{construct feasible path(s) in } P\}$

$Q \leftarrow Q \cup \{\text{short delay path in } F\}$

if F contains only one path from s to r **then**

 Return the path in Q with smallest weight

else if F contains two paths from s to r **then**

 Let p_s and p_l be the paths

 Add constraint according to (20) to the LP

 Solve the LP with the additional constraint

$P \leftarrow$ solution of the updated LP

if P is infeasible && $Q = \emptyset$ **then**

 No feasible path exists

 Initiate direct cellular communication between BS and r

else if $Q \neq \emptyset$ && $\{\exists P' \in Q | C(P') < C(B2D)\}$ **then**

 Return the path in Q with smallest weight and cost < B2D

else

 Initiate direct cellular communication between BS and r

events such as appointments force them to make a long distance trip even in the presence of unvisited nearby destinations. SLAW leverages this self-similarity of fractal waypoints, which can be viewed as destinations, to realistically predict the human mobility. In this paper, we have used the similar parameter settings for capturing this regularity in human mobility patterns which are also suggested in the original paper [23]. The wireless propagation channel is modeled for urban macrocell scenarios with shadowing component set to having standard deviation of 12 dB and path loss exponent α set to 3. The cell area is set up as a $1 \text{ km} \times 1 \text{ km}$ square with the BS at its center. The noise spectral density is -174 dBm/Hz . The transmit power for each device is 100 mW whereas the power of the BS is set to 10 W. The total bandwidth of the RBs are set to 5 MHz in accordance with LTE RBs [24] and the maximum D2D distance is set to $d_{max} = 15 \text{ m}$. The main wireless network parameters are listed in Table IV. We have set ρ , ζ and δ to 0.8, 0.7 and 4 respectively in constructing G_p for durable community detection. We describe how to choose these values later in this section.

TABLE IV: Main Wireless Network Parameters

Notation	Description
Cell dimension	1000 x 1000 m^2
BS location	Center of the area
Shadowing std. dev.	12 dB
Path Loss Exponent	3
Noise spectral density	-174 dBm/Hz
BS transmit power	10 W
D2D transmit power	100 mW
Maximum D2D distance	15 m
RB size	12 sub-carriers, 0.5 ms

We have compared the performance of our solution, RPF, with Groups-NET (GNET in short) which is a mobility-aware social-based approach that analyses the impact of device mobility on the cellular network performance and multi-hop D2D in particular [25]. GNET identifies social groups based on previous social meetings. It then computes the likelihood of each group meeting in future by computing the group-to-group paths by considering the meeting regularity and shared group members. Finally, it identifies the most probable path from the source to the destination by leveraging the group-to-group path probability. It has been shown that GNET outperforms other state-of-the-art methods in terms of improving the cellular network efficiency [25]. We also compare our results with two other social-oblivious methods: i) minimizing cost (MC) scheme that chooses devices that minimize the cost of the BS in content transmission, ii) closest to destination (CD) scheme that selects the device that is physically closest to destination at each hop. These greedy methods have been used for relay selection in multi-hop D2D as an efficient way to offload cellular traffic and to enable content transfer through D2D when direct connection can not be established between the source and the destination.

We generated location of total 400 users in the designated area using SLAW model for 72 hours and used first $\Delta t = 48$ hours for detecting the social encounter based communities. The rest 24 hours were used for simulating the D2D content transfer. We randomly chose 20 cellular users uniformly distributed over the area and 20 pairs of D2D devices as source and target (having distance larger than d_{max}) and averaged the results over a large number of independent

simulation runs.

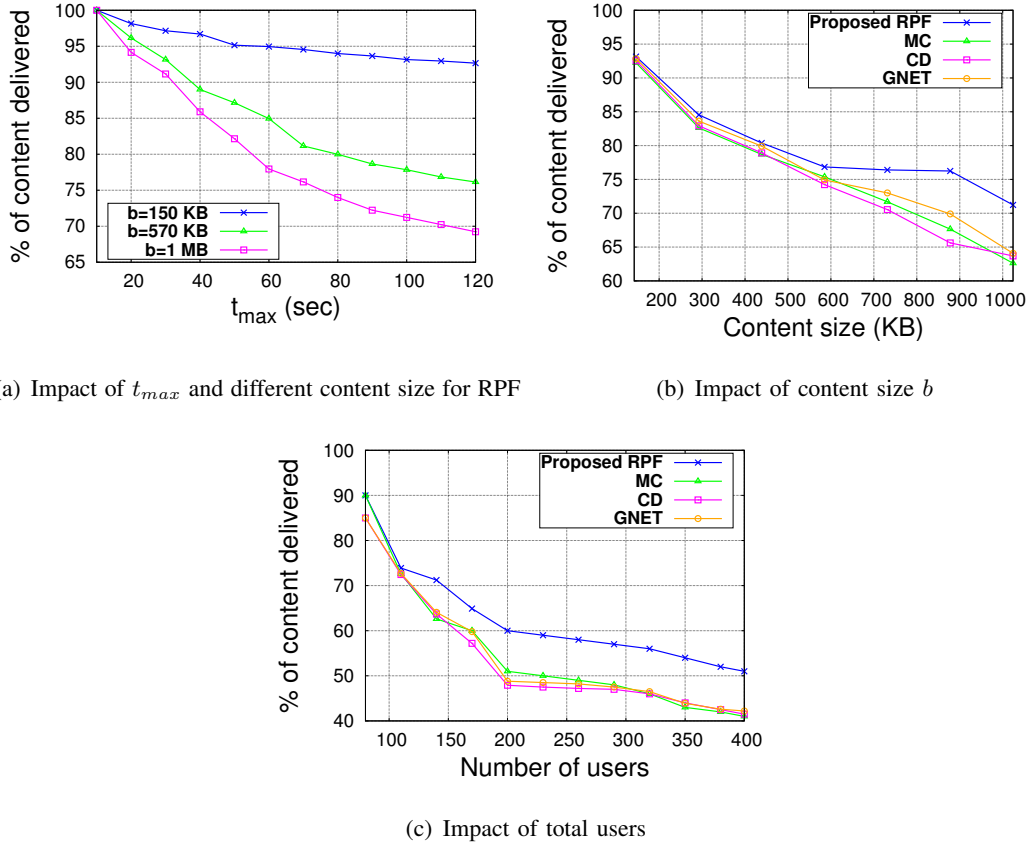


Fig. 3: Content transmission success rate for different cases

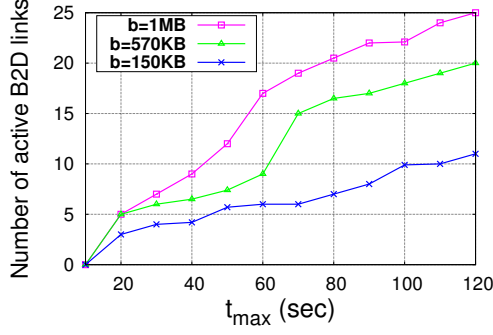
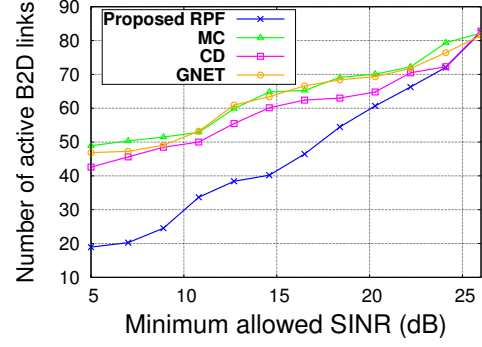
Fig. 3 compares the content delivery rate for the proposed algorithm and the baseline approaches when different parameters are varied. In Fig. 3(a), we show the content delivery rate achieved by our proposed algorithm RPF for 140 users and three different content sizes 150 KB, 570 KB, and 1 MB as the content sharing time t_{max} is varied from 10 s to 120 s. For a particular content size b , with increasing t_{max} , the RPF tends to choose devices on the multi-hop path with delivery time close to t_{max} so as to minimize the cost. This results in more hops on a multi-hop D2D path, thus making it more susceptible to device mobility. Consequently, the content delivery success rate keeps decreasing with larger values of t_{max} . However, RPF chooses the same multi-hop path after certain value of t_{max} as the path cost can no longer be minimized within t_{max} . From the Fig. 3(a), we can see that the delivery success rate remains

at around 70% after t_{max} reaches 120 s for content size $b = 1$ MB. For a particular t_{max} value, the delivery success rate decreases with larger content size. Larger content requires more time to be transmitted which makes them more prone to device mobility. Therefore, a larger content size results in reduced content delivery rate for a fixed t_{max} which is also evident from the Fig. 3(a).

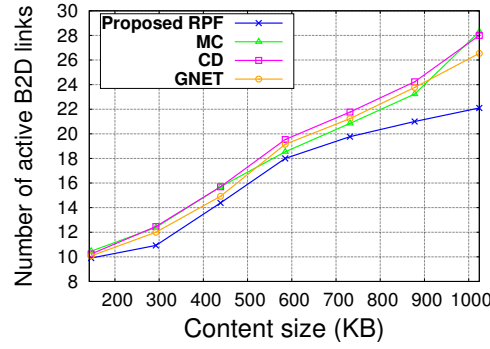
In Fig. 3(b), we show how varying the content size impacts the content delivery rate when t_{max} is set to 100 s for 140 users. Clearly, as content size increases, the delivery rate decreases. However, the rate of degradation for RPF is much smaller than other methods. This is due to the fact that larger contents require more time for transmission which, in turn, makes the longer D2D session more susceptible to device mobility. In such cases, the mobility of the devices can lead to premature tear down of the multi-hop D2D session. As a result, methods that do not account for social communities in choosing reliable devices on multi-hop will experience a poor delivery rate. Fig. 3(b) shows that the content delivery rate is up to 14% higher for the proposed RPF algorithm when compared to the social-unaware scenario for $b = 1$ MB.

Fig. 3(c) shows how the content delivery rate varies with the network size. As the number of users increases, one expects a better delivery rate due to more option for multi-hop. However, a large number of users will also increase interference for users that need to transmit on the same RB. In such a scenario with scarce resources, achievable data rate decreases leading to longer transmission time which makes them more susceptible to device mobility. Interestingly, RPF suffers less from the increased user concentration which makes it best device selection method. In Fig. 3(c), we can see that the proposed RPF is more resilient to mobility than all other approaches. Moreover, the content delivery rate resulting from RPF is up to 24% higher than the social-unaware scenario for a user count of 400.

Furthermore, from Figs. 3(a)-3(c), we can see that all the baseline methods perform poorly compared to RPF in terms of content delivery success rate. On the one hand, for CD, since it does not consider the signal and noise information, it suffers from poor content delivery. On the other hand, MC always tries to minimize the BS cost which, in some cases, results in choosing devices that require large time to deliver thus making it prone to experience disconnections during mobility. GNET also suffers from poor delivery rate as it prioritizes the most probable community-to-community path. Two adjacent devices belonging to two different communities with large community-to-community path probability will be chosen by GNET, even if they

(a) Active B2D links vs t_{max} 

(b) Active B2D links vs SINR



(c) Active B2D links vs content size

Fig. 4: Offload performance analysis for different cases

have never met before. As a result, these devices without significant previous meeting records, might move far apart from each other during a transmission session leading to poor delivery of content. On the other hand, RPF's consideration of durable social communities enables it to identify devices that are likely to maintain the required QoS during the whole session by remaining close to one another.

Fig. 4 evaluates the offload performance of the proposed RPF. For a 100 seconds duration, we recorded the number of active B2D links in the network which is shown in Figs. 4(a)-4(c). The BS initiates a direct cellular connection towards the target when: a) there is no feasible multi-hop path or b) the multi-hop device cost is larger than the direct BS to device (B2D) cost or c) the mobility of devices on a path leads to a premature disconnection of that path.

Fig. 4(a) shows the impact of increasing t_{max} as contents of three different sizes 150 KB, 570 KB, and 1 MB are transmitted. Since contents can be transmitted for a longer duration with increasing t_{max} , the number of active B2D links increases for each of the content size b . This corroborates the intuition that the mobility of devices may disrupt D2D sessions which will require the BS to use costly B2D links. As the content size increases, more time is needed for content transmission which, in turn, makes the multi-hop D2D path more prone to device mobility. Consequently, the premature tear down of an ongoing session due to device mobility leads to the reliance on increasing number of B2D links where the content is served directly by the BS to the content requester.

In Fig. 4(b), we can see the impact of minimum allowed SINR on network traffic offload. In case of smaller SINR, devices can sustain longer D2D sessions since the required QoS for such a communication is low. This results in more successful content delivery over multi-hop D2D which, in turn, requires less number of B2D links. However, when the allowable SINR is increased, the tolerance to device mobility is decreased which subsequently results in more active B2D links. From Fig. 4(b), we can see that the other methods require as high as 158% more B2D links compared to the proposed RPF for a target SINR of 5 dB.

In Fig. 4(c), we show the comparative performance of different relay selection methods for varying number of content size from 150 KB to 1 MB for a fixed network of size 140 and $t_{max} = 100$ s. As content size increases, all methods will start to increasingly rely on the B2D links. However, RPF requires 28% less B2D links compared to other methods. The reduction in the number of B2D links demonstrates the improved offload capabilities of the proposed RPF. Such an offload of traffic from the BS to the D2D tier also reduces the usage of expensive backhaul traffic.

In Fig. 5, we show the percentage of time a multi-hop D2D path is chosen instead of an expensive direct B2D link for a user count of 140. This figure also gives an indication on the quality of the cost functions that we have defined in (4) and (5). Note that, this comparison considers only the cost of direct B2D and D2D relay devices before the transmission starts. Fig. 5 shows that, over 90% of the time, the RPF chooses multi-hop D2D due to its cost-effectiveness. The small portion of time during which the direct B2D links are used is primarily due to the destination devices which are closer to the BS and can receive the content directly from the BS with low cost. As the allowed t_{max} increases, more D2D links are chosen by RPF compared to

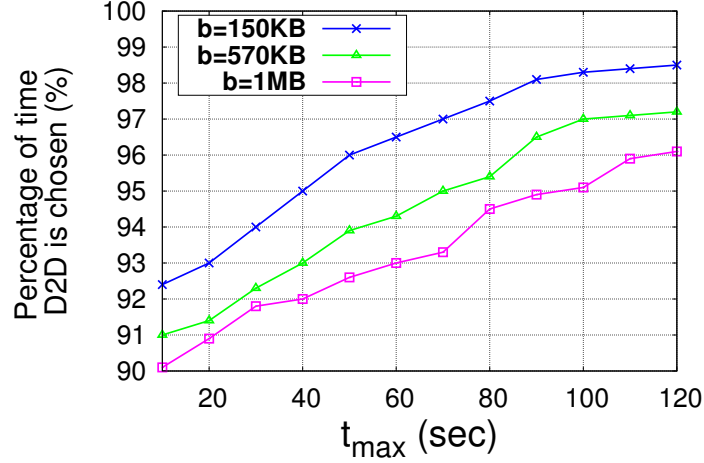


Fig. 5: Cost-effectiveness of multi-hop D2D for three different content sizes and a range of t_{max}

B2D links. With increasing t_{max} , the RPF tends to choose devices on the multi-hop path with delivery time close to t_{max} as it tries to minimize the cost. This results in a D2D path having a smaller cost, which explains why more D2D links are selected by RPF as the t_{max} increases for a particular content size. Furthermore, as the content size increases, the chances of forming better (less expensive) D2D path starts decreasing. For a given t_{max} , RPF has to choose devices of higher cost as the content size b increases in order to find a D2D path that is capable of delivering the content within t_{max} . Therefore, a larger content size results in decreased percentage of D2D links being chosen by RPF before the content transmission starts as shown in Fig. 5.

Fig. 6 shows the execution time needed for our approach. RPF achieves the optimal solution within shortest possible time even in large networks. In almost all realizations, it takes less than a second on the average to compute cost-effective devices on multi-hop path. We performed all the computations on an AMD Opteron(tm) Processor 6168 CPU with 64 GB-memory Linux machine.

In Fig. 7, we show the impact of different parameters mentioned in Subsection III-B1 on the performance of the RPF algorithm. Fig. 7 is the heat map representing the impact of δ (stability threshold) and the weight factor ρ on the content delivery success rate achieved by RPF for a user count of 140, content size $b = 1$ MB, and $t_{max} = 100$ s. The success rate is depicted by the RGB colors. As the success rate gets higher, the color becomes lighter in the heat map. From

Figure 7, we can see that the color is lightest, i.e., the contents are successfully delivered, in the top right corner where $\rho = 0.8$ and $\delta = 4$. The content delivery success rate increases till $\delta = 4$ and starts deteriorating as δ is increased further. Accordingly, we assign the values of ρ and δ to 0.8 and 4 respectively for this setup of user count, content size and t_{max} . We vary the value of strength threshold ζ from 0.5 to 0.9 and choose $\zeta = 0.7$ as RPF achieves better content delivery with this setup.

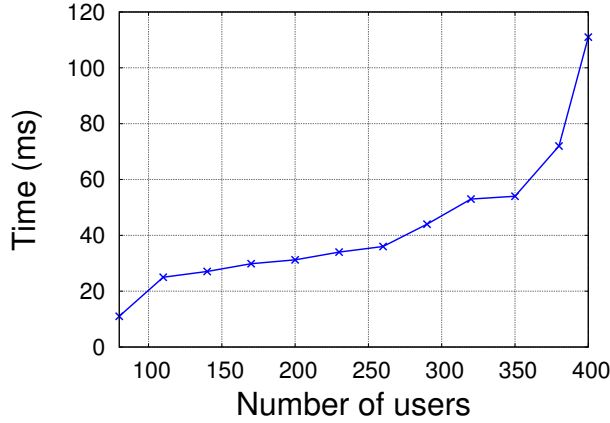


Fig. 6: Execution time of RPF

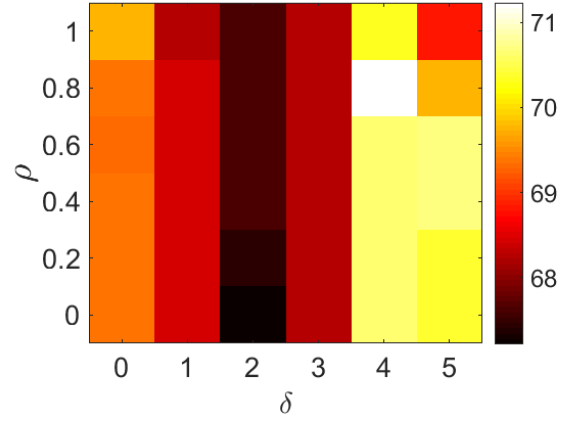


Fig. 7: Impact of different parameters for constructing G_p on the performance of RPF

In Fig. 8, we show how the cost of the BS varies with total users in the network. The BS cost is normalized by the highest cost attained for the maximum user count. It is clear that the BS cost for RPF is smaller than that of any other methods. Although, MC aims to choose relay devices that yield a minimum cost, it suffers from poor delivery since it does not take the mobility of devices into account. Therefore, the BS has to invoke expensive B2D links to deliver the content resulting in increased BS cost as evident from the Fig. 8. The other two methods also results in a higher BS cost as they also fail to consider devices' mobility while choosing relay devices. For all of the methods, as the number of users increases so does the interference originating from users that are sharing same resources. In such a scenario, similar to what we have seen in Fig. 3(c), achievable data rate decreases due to scarce resources. This, in turn, leads to longer transmission time which makes them more susceptible to device mobility and consequently results in higher BS cost. However, as the user count increases, the gap between

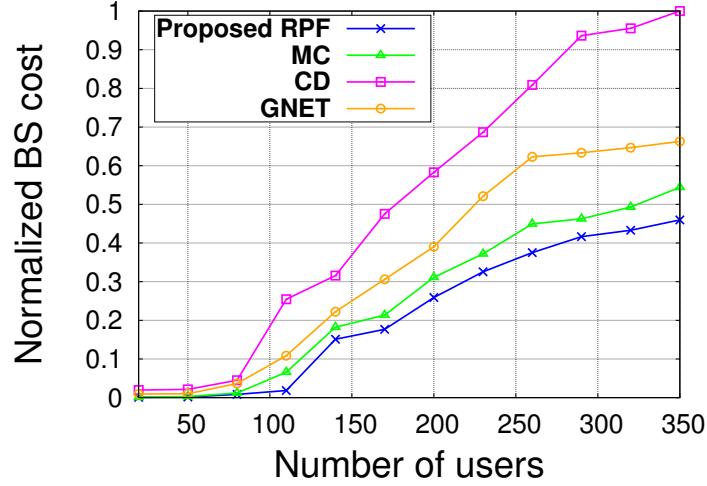


Fig. 8: The cost of the BS vs user count

RPF and other methods also increases validating the superiority of our method in terms of minimizing the BS cost.

VI. CONCLUSION

In this paper, we have studied the impact of device mobility on the performance of multi-hop D2D underlying cellular network. We have introduced a novel model that considers durable communities based on the social encounters of devices for predicting the likelihood of devices' proximity. We have formulated the reliable device selection problem as an IP optimization problem and we have proposed an efficient heuristic algorithm to solve it. We have also shown that leveraging social communities can increase the content delivery rate in multi-hop D2D. Simulation results show that our proposed method outperforms classical social-unaware methods significantly in terms of traffic offload. The results also show that the proposed method achieves its objectives with manageable computational complexity which makes it applicable to larger networks.

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